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DEMENTIA RISK ASSESSMENT USING MACHINE LEARNING AND PART-OF-SPEECH TAGS

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ABSTRACT

Dementia, a set of cognitive decline syndromes distinct from typical age-related degeneration, poses a significant public health challenge. The key to dementia detection lies in analyzing sentence structure and conversational style, particularly in speech. This study focuses on creating and evaluating a machine learning model for non-invasive early dementia detection through speech parameter analysis in everyday conversation. Leveraging the DementiaBank dataset, comprising over 500 voice transcripts from individuals aged 60 and older, the study employs 63 tagged Part-of-Speech (PoS) parameters extracted from chat transcripts. Data from 244 control subjects and 306 dementia patients are used. Machine learning methods, including Random Forest, Deep Neural Network, and Support Vector Machine, achieve respective accuracy rates of 83%, 92%, and 84%. These results underscore the effectiveness of informatics-based machine learning in non-invasive dementia detection using PoS tags. Additionally, the study provides insights into the relative importance of each PoS tag in dementia detection. This research contributes to the growing informatics field of dementia detection and supports the development of less intrusive diagnostic tools.

Keywords: *Machine Learning, Dementia, Speech, Linguistics, Part-of-speech*

1. INTRODUCTION

Dementia is a syndrome characterized by the progressive decline in memory, cognitive function, behavior, and daily life skills [1]. While it predominantly affects the elderly, it should not be misconstrued as a natural part of aging. Globally, approximately 50 million individuals suffer from dementia, with nearly 10 million new cases arising annually [2]. It ranks among the leading causes of disability and dependency among older populations worldwide, posing significant challenges to affected individuals, their caregivers, and families. Healthcare practitioners identify potential signs and symptoms of dementia, such as forgetfulness, disorientation, apathy, and emotional instability. If these indicators are present, they assess impairment in daily activities like social interactions, financial management, cooking, and personal care, signaling the onset of dementia. Clinicians conduct a comprehensive medical evaluation, encompassing physical examinations, medical history, functional assessment, and vital statistics. When deficits are detected, clinicians explore treatable causes of dementia through medication, addressing depression, and utilizing laboratory tests for biomarker identification [3]. The recommended course of action for persistent dementia symptoms depends on its severity. For mild impairment, regular reassessment every six months is advised. In cases of more pronounced symptoms, standard dementia treatment protocols are initiated.

Notably, language impairments often serve as one of the initial cognitive indicators of Dementia onset. Individuals with dementia often exhibit issues with word retrieval (anomia), comprehension deficits in sentences, and a lack of coherence in their dis-course [3,4]. We aim to utilize this aspect of speech degeneration to create a machine learning framework for early detection of dementia.

Previous research in this area has mainly focused on different techniques like audio processing, statistical methods, advanced neural networks, and complex language models for prediction purposes. In contrast, our method stands out by highlighting the innovative use of Part-of-Speech tags as a crucial factor in detecting dementia.

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2. BACKGROUND

Research into analyzing speech characteristics to detect cognitive decline associated with dementia has been an ongoing field of study.

2.1 Related Work

Ablimit, A. et.al.[5] established speech as a reliable indicator of cognitive decline. This premise is augmented by studies conducted by Reeve et al. [6], which demonstrated speech degradation and verbal repetition as exhibited due to the onset of dementia. Continuing in this vein, Baldas et. al [7] explored continuous speech quality as an indicator of cognitive decline. Farzana et al. [8] emphasized the significance of involuntary disfluency in predicting dementia. A Part of Speech was categorized as 'disfluent' when it contained verbal fillers such as "uh" and "um". Sweta Karlekar et al. [9] found that the use of NID words (Not in Dictionary), pronouns, definite articles, and determiners, such as "the" and "that," were amplified in dementia patients. Ali Khodabakhsh et al. [10] delved into qualitative speech features, including the filler ratio, incomplete sentence ratio, and the use of rich-textured speech, to ascertain cognitive decline. Filler sounds like 'ahm' and 'ehm' often appear when individuals are thinking about what to say next. Incomplete sentences were manually labeled for each conversation.

Furthermore, Berisha, V., Wang, S., LaCross, A., & Liss, J. [11] conducted a similar exercise, studying press conferences of U.S. Presidents Ronald Reagan and George Herbert Walker Bush. Their study identified a decrease in the use of specific nouns and an increase in non-specific nouns as these presidents aged. This is highlighted in Figure 1. Forbes-McKay K et al. [12] discussed detecting subtle spontaneous language decline in early Alzheimer's disease using a picture description task. The subject of the test was asked to describe the picture. Deficits were detected even in the very early stages of the disease. Antonsson et al. [13] also contributed to this area by using statistical methods to analyze discourse features, improving classification accuracy, and discriminating between participants with stable cognitive impairment and those who had cognitively declined. Four clear factors emerged: semantic impairment, acoustic abnormality, syntactic impairment, and information impairment. This suggests that modern machine learning and linguistic analysis are increasingly valuable for assessing and clustering suspected cases of Alzheimer's disease. Additionally, Matosevi L [14] and Balgoplan [15] applied pretrained language models to explore the potential of linguistic features. Fraser et al. highlighted the significance of linguistic features, some of which can be expressed through audio signals. Kumar, M et. al. [16] conducted audio analysis to create a machine learning model for predicting dementia detection. Linguistic features can also be visualized as logical structures classified using lexical features. Kong [17] and Zhu et al. [18] explored the potential of neural networks in establishing dementia prediction from language. Meanwhile, Martinc et al. [19] and Parsapoor [20] combined acoustic and textual analysis to provide a theoretical model for predicting dementia using speech.

Literature supports the notion that Dementia affects the distribution of Part-of-Speech. Williams E and Theys C [21] demonstrated that the utilization of nouns (n) significantly contributes to predicting dementia risk. Bittner, D et al [22] noted that the usage of personal pronouns (pro: per) likewise exerts a significant impact on dementia risk prediction. Additionally, research conducted by Xuan Le et al. [23] suggests that the proportion of adverbs also influences dementia prediction.

2.2 Rational for this work

Section 2.1 lays the groundwork for our research by presenting a strong rationale for the exploration of machine learning in conjunction with language features for predicting dementia. In this study, we adopt a diverse set of machine learning techniques to scrutinize speech features, aiming to gain valuable insights from the models we employ.

Findings of Previous Studies

Earlier studies in this domain have largely focused on diverse elements like processing audio signals, applying statistical techniques, using intricate neural networks, and employing advanced language models for predictive tasks.

Contribution of our Work

Our method sets itself apart by underscoring the novel application of Part-of-Speech tags as a key component in dementia detection. We employ Part-of-Speech tags due to their computational simplicity, which leads to quicker model responses. Additionally, these tags provide a clear and verifiable explanation of the model's reasoning process, aligning with domain expertise.

In summary, Section 2.1 not only justifies our research focus on the application of machine learning to language features for dementia

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prediction but also underscores the novelty and innovation in our choice to concentrate on Part-of-Speech tags as a key element in this endeavor.

3. RESEARCH METHODOLOGY

3.1 Nature of Input Data

We utilize the DementiaBank dataset, which comprises of chat transcripts of individuals aged 60 and above, meticulously curated by the University of Delaware Institutional Review Board in the United States. To gain access to this dataset, one can make a formal request to the DementiaBank research committee through their website (https://dementia.talkbank.org/ as accessed on May 15, 2023). From the DementiaBank Dataset, we specifically use Pitt Corpus Transcripts. These transcripts encompass the spoken narratives of individuals performing four distinct tasks: describing a picture, narrating a story, engaging in procedural discourse, and sharing personal narratives. Our primary focus is on the subset of transcripts that pertain to the description of the "Cookie Theft" picture (indicated in Figure 2), as presented in the protocol by Goodglass and Caplan [24].

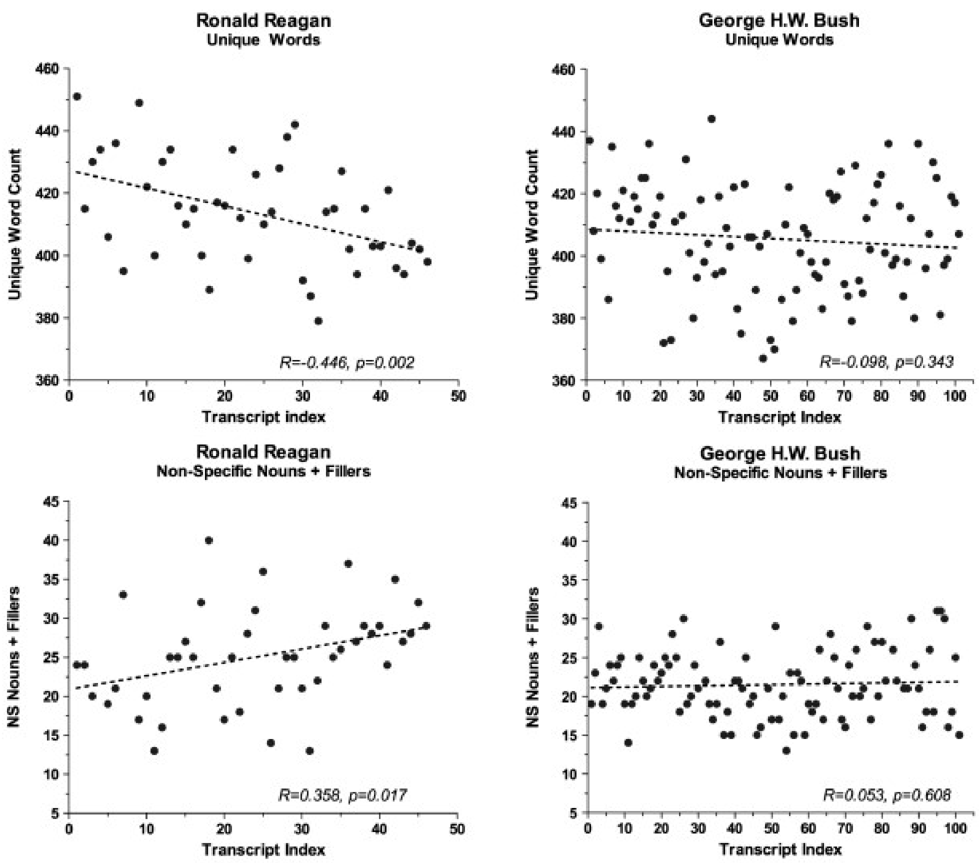

Figure 1. Scatter Plot for distribution of Unique Word Count and Non-Specific Nouns from the work of Berisha, V., Wang, S., LaCross, A., & Liss, J. [11]

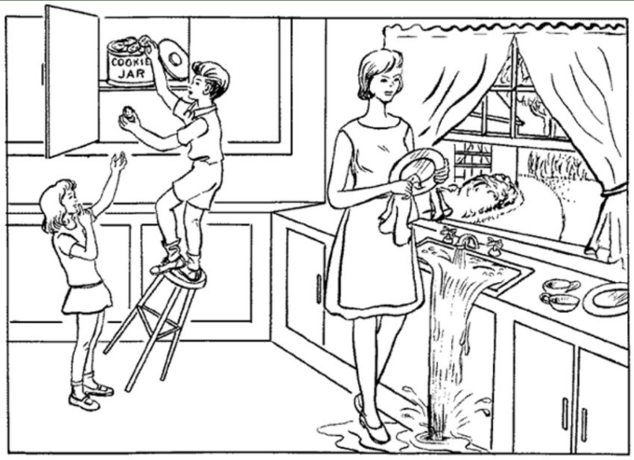

Figure 2. Cookie Theft Picture[24]

In this subset, subjects were prompted to describe the picture with the following instruction: "Please tell me everything you see going on in this picture." The speech of the subjects describing the picture was meticulously transcribed by a trained researcher and subsequently cross-verified by a secondary researcher to ensure reliability. Detailed information about DementiaBank methodology and principals can be found in the publications by Becker, J. [25] and Lanzi et. al. [26]. Additionally, for different corpus, work of MacWhinney, B. et. al.[27] can be explored.

3.2 Our Methodology

In this section, we offer a comprehensive breakdown of the methodology employed for creating Machine Learning models from the chat transcripts. This encompasses the entire process, beginning with the initial data parsing and continuing through to the development of the machine learning model.

Step 1: We use 550 chat transcripts of cookie theft corpus; out of which 244 are neuro-typical (people not affected with dementia) referred as control persons and 306 people affected by dementia. The chat transcripts are available in '.cha' format. The raw view of chat transcript is as shown in Figure 3.

Step 2: In order to convert the raw format into structured data, we use pylangacq library in python to parse these chat transcripts. When we parse the chat transcripts, we get list of `tokens`, which is a data structure that contains meta information about each word. Hence for each word, we get information as shown in Table 1.

Table 1: This table represents the structure of `Token` object generated for each word.

Data Field	Description	Example
Word	The original word that this token represents	Seem
Part of Speech Tag	Tag that represents what part of speech the word is	`cop` - copula a form of verb
Morpheme	Smallest significant for of word	Seem

Step 3: After aggregating all the tokens from the chat transcripts, we analyze the base corpus of Part-of-Speech (PoS) tags available to us. List of all PoS tags extracted are as highlighted in Table 2.

Table 2: Sample List of PoS Tags

Tag	**Description**
!	Exclamation Mark - Indicates strong feelings or emphasis.
+"., +/`	Prosodic or intonational features.
+.	Prosodic or intonational features.
+...	Prosodic or intonational features.
+..?	Prosodic or intonational features.
+/.	Prosodic or intonational features.
+//.	Prosodic or intonational features.
+//?	Prosodic or intonational features.
+/?	Prosodic or intonational features.
.	Period - Indicates the end of a sentence.
?	Question Mark - Indicates a question.
Adj	Adjective - Modifies or describes a noun.

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Adv	Adverb - Modifies a verb, adjective, or adverb.
adv:tem	Temporal Adverb - Indicates a specific time.
Aux	Auxiliary Verb - Helps another verb express tense, mood, etc.
Beg	Beginning - Indicates the start of a sentence or turn.
Cm	Comment Marker - Indicates a comment or aside.
Co	Coordinating - Coordinating element, possibly a conjunction.
comp	Complementizer - Introduces a subordinate clause.
conj	Conjunction - Connects words, phrases, or clauses.
coord	Coordination - Indicates coordination between elements.
Cop	Copula - Links subject to subject complement.
det:art	Article Determiner - Specifies noun definiteness (e.g., "the").
det:dem	Demonstrative Determiner - Points to a specific noun (e.g., "this").
det:num	Numeral Determiner - Indicates a number or quantity.
det:poss	Possessive Determiner - Indicates ownership (e.g., "my").
End	Ending - Indicates the end of a sentence or turn.
grand#n	Possibly refers to a "grand noun." Unclear without context.
in#adj	Adjective with "in-" prefix.

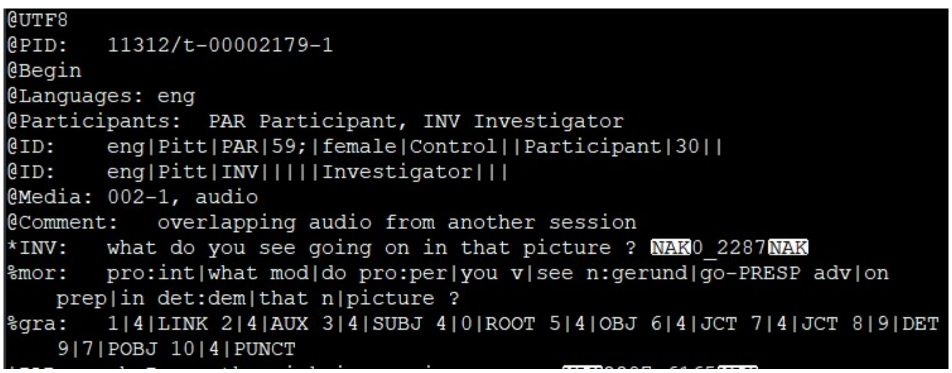
```
@UTF8
@PID:   11312/t-00002179-1
@Begin
@Languages: eng
@Participants:  PAR Participant, INV Investigator
@ID:    eng|Pitt|PAR|59;|female|Control||Participant|30||
@ID:    eng|Pitt|INV|||||Investigator|||
@Media: 002-1, audio
@Comment:   overlapping audio from another session
*INV:   what do you see going on in that picture ? NAK0_2287NAK
%mor:   pro:int|what mod|do pro:per|you v|see n:gerund|go-PRESP adv|on
    prep|in det:dem|that n|picture ?
%gra:   1|4|LINK 2|4|AUX 3|4|SUBJ 4|0|ROOT 5|4|OBJ 6|4|JCT 7|4|JCT 8|9|DET
    9|7|POBJ 10|4|PUNCT
```

Figure 3. Raw Format of Chat Transcript as viewed in a simple text editor software.

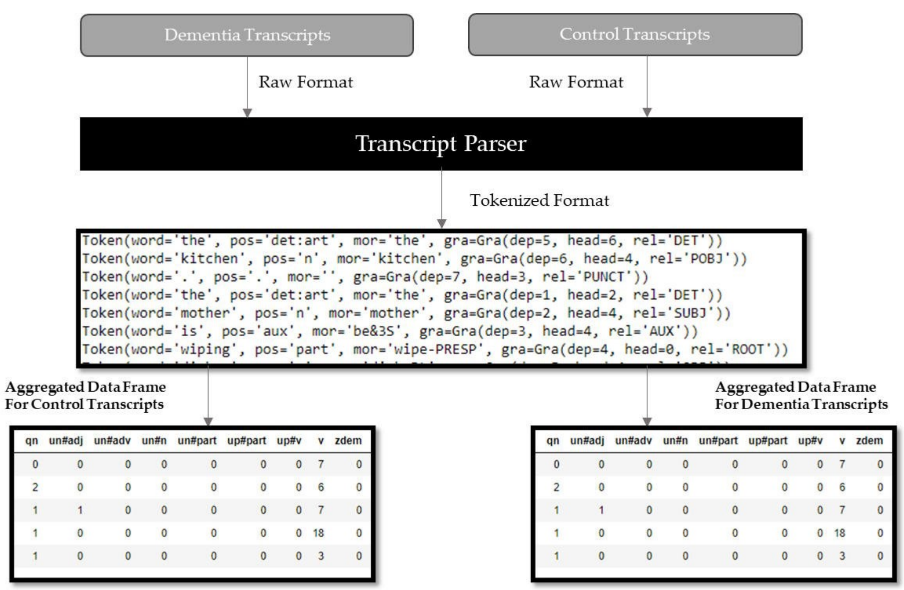

Figure 4. Flow Chart for transcription aggregation

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	!	+".	+"/.	+.	+...	+..?	+/.	+//.	+//?	+/?	...	qn	un#adj	un#adv	un#n	un#part	up#part	up#v	v	zdem
0	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	7	0
1	0	0	0	0	0	0	0	0	0	0	...	2	0	0	0	0	0	0	6	0
2	0	0	0	0	0	0	0	0	0	0	...	1	1	0	0	0	0	0	7	0
3	0	0	0	0	0	0	0	0	0	0	...	1	0	0	0	0	0	0	18	0
4	0	0	0	0	0	0	0	0	0	0	...	1	0	0	0	0	0	0	3	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
304	0	0	0	0	0	0	1	0	0	0	...	0	0	0	0	0	0	0	5	1
305	0	0	0	0	1	0	0	0	0	0	...	0	0	0	0	0	0	0	9	1

Figure 5. Data frame of Part-of-Speech tags and Subjects

Step 4: For each subject in the picture description task, we calculate the frequency of each Part of Speech (PoS) tag by analyzing all the tokens present in the chat transcript.

Step 5: We structure the data frame in a manner where each column corresponds to a specific part of speech, each row corresponds to one test subject and each cell in the data frame contains the count of tag associated with that specific subject.

Step 6: We introduce an additional label, 'zdem,' that acts as an indicator for dementia status in the subject. The assignment of this 'zdem' value depends on the chat transcript's location within the foundational dataset. More precisely, transcripts from dementia patients are in the 'dementia' folder, while those from control subjects (individuals without dementia) are housed in the 'control' folder. This setup aligns with one of the primary objectives of our chosen machine learning method, which is binary classification. This process is summarized in Figure 4.

Step 7: We merge the two data frames obtained from `control` and `dementia` folders, into a single frame that would serve as our training data. The structure of the data frame is as shown in Figure 5.

Step 8: In the data refinement process, we took measures to enhance the quality and relevance of our dataset. Specifically, we removed rows wherein the count of speech tags was found to be zero for more than 60% of the observations. This meticulous curation resulted in a dataset comprising 458 samples. Additionally, we carried out the elimination of Parts of Speech (PoS) tags that exhibited a count of zero across all sub-jects. Following this comprehensive data cleaning procedure, our dataset was refined to include a total of 60 unique PoS tags.

Step 9: Subsequently, to ensure a robust assessment of model performance and generalization, we partitioned the dataset using an 80:20 split ratio. This partitioning strategy involved utilizing 80% of the randomized data for training purposes, while re-serving the remaining 20% of the data to serve as an independent test set for evaluation.

Step 10: Choice of Machine Learning Methods: The purpose of this study extended beyond the mere acquisition of a classification model for predicting risk; it also aimed to gain deeper insights into the underlying mechanisms driving dementia classification outcomes. We opted for the random forest algorithm as one of our choices for classification. This selection was motivated by the fact that the random forest algorithm not only provides a classification model but also offers valuable information regarding the relative importance of each input parameter within the model.

At the core of the random forest algorithm lies the decision tree, a fundamental component in machine learning. The decision tree algorithm constructs a hierarchical model resembling a tree, which facilitates decision-making and prediction. It operates through iterative division of the dataset into smaller subsets, leveraging the most informative features to create a tree structure. In this structure, each internal node represents a decision based on a specific feature, while each leaf node corresponds to an outcome or prediction [28]. Random forest, on the other hand, is an ensemble machine learning technique that enhances predictive accuracy while addressing the issue of overfitting. It achieves this by combining multiple decision trees. The algorithm accomplishes its task

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by training numerous decision trees on random subsets of the dataset and then aggregating their predictions. Each individual tree within the forest makes independent predictions, and the final output is determined through a majority vote (in the case of classification) or an averaging process (for regression) [29].

We also developed a second model employing an artificial neural network (ANN). This secondary approach was utilized to assess the comparability of our random forest model's accuracy. It's worth noting that ANNs, being considered "black boxes," do not provide insights into the significance and influence of input parameters. The architecture of the neural network is as shown in Table 3.

Table 3: This table represents the structure of `Token` object generated for each word.

Layer #	Neuron Count	Activation
Layer 1	60	ReLu
Layer 2	60	ReLu
Layer 3	1	Sigmoid
Parameter	**Info**	
Input Shape	60	
Batch Size	25	
Steps per Epoch	15	
Validation Steps	7	
Test Steps	7	

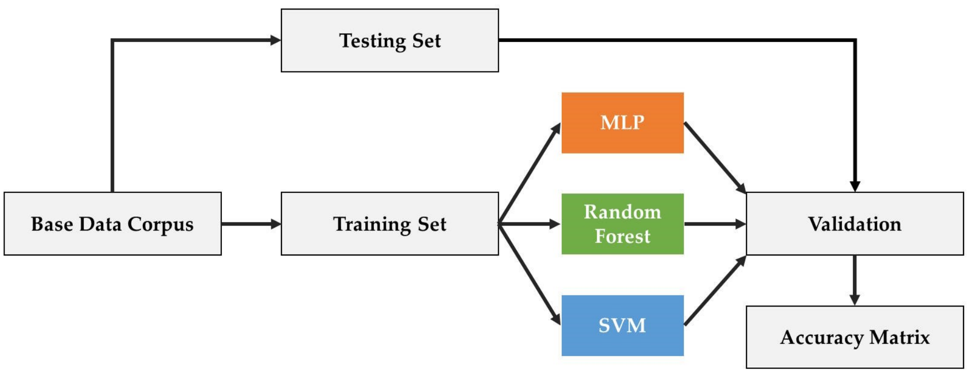

Figure 6. Training Framework

This architecture is commonly known as a feedforward neural network or a multi-layer perceptron (MLP). It represents a form of artificial neural network in which information proceeds unidirectionally, starting from the input layer, passing through one or more hidden layers (in our case, consisting of 2 hidden layers, each containing 16 neurons), and ultimately reaching the output layer, which consists of 1 neuron with sigmoid activation [30]. For our neural model, we employed the 'Adam' optimizer to expedite convergence toward the minima. Additionally, we selected the sigmoid activation function for the output layer, as it is particularly well-suited for binary classification tasks [31]. We use Support Vector Machine (SVM) as our third machine learning method. This method uses quadratic equations to create sample hyperspace to classify input data into different categories [32].

4. RESULTS

Table 4 highlights results we obtained after we ran these models. The description of the terms is listed in Table 5.The framework for our methodology is as shown in Figure 6.

Table 4: Accuracy Matrix: TP-True Positive, TN-True Negative, FP-False Positive, FN-False Negative

Method	sample count	TP	TN	FP	FN	Accuracy	Recall	Precision	F-Score
MLP	458	158	264	14	22	0.92	0.88	0.93	0.90
SVN	458	175	212	36	35	0.84	0.83	0.83	0.83
Random Forest	458	145	235	35	43	0.83	0.77	0.81	0.79

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Table 5: Information about terms related to accuracy.

Term	Description
Precision	Precision is the ratio of true positive predictions to the total number of predicted positives.
Recall	The ratio of true positive predictions to the total number of actual positives is termed 'recall'.
F1-Score	The F1-score is the harmonic mean of precision and recall.
Accuracy	Accuracy is the ratio of correctly predicted instances to the total number of instances. It gives an overall measure of how well the model performs across all classes.
Macro Avg and Weighted Avg	These are averages of precision, recall, and F1-score calculated across all classes. Macro average treats all classes equally, while weighted average takes class imbalance into account.
TP	True Positive Count
TN	True Negative Count
FP	False Positive Count
FN	False Negative Count

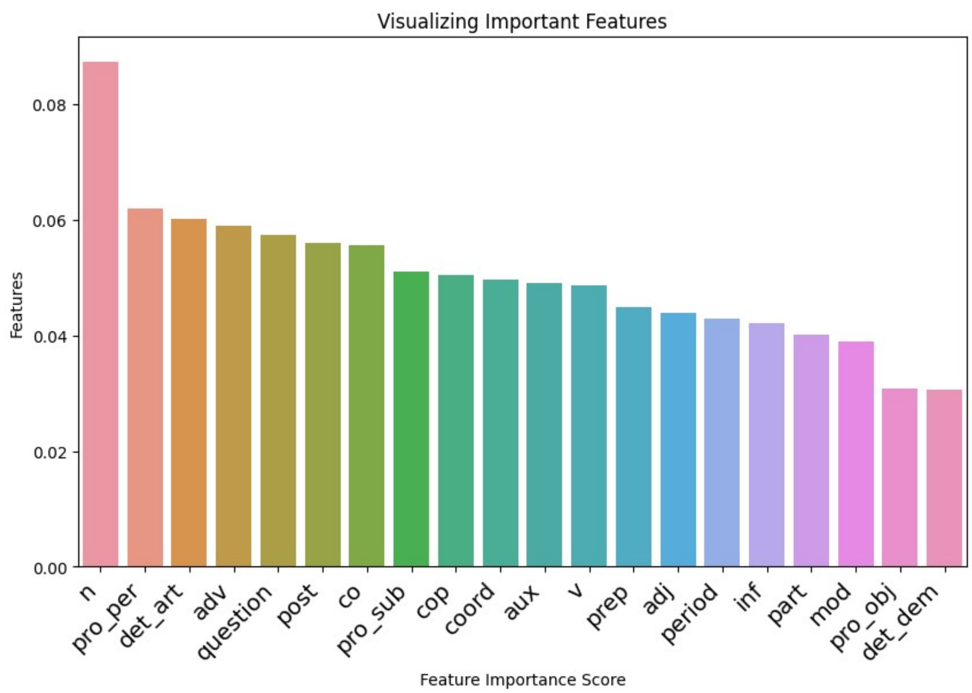

Figure 7. Data frame of Part-of-Speech tags and Subjects

MLP provides with highest accuracy of 92% followed by SVM (84%) and Random Forest (83%). Random forest also furnishes us with supplementary insights into the significance and influence of PoS tags in predicting the risk of dementia. Figure 7 highlights relative feature importance. Table 6 presents the ten most influential features in predicting dementia.

Table 6: Top 10 impactful features

Rank	Feature
1	Noun (n)
2	Personal Proposition (pro:per)
3	Determiners (pro:det)
4	Adverb (adv)
5	Question (q)
6	Post-Position Noun Descriptors (post)
7	Co (conjunction)
8	Subject Pronoun (pro: sub)
9	Copula - Links subject to subject complement. (cop)
10	Coordination - coordination tag

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5. DISCUSSION

The functional task of describing the cookie theft picture (as illustrated in Figure 2) provides a non-intrusive and conversational method for gathering lexical information. By applying machine learning methods to the Parts-of-Speech tags extracted from this lexical data, we can gather significant insights into the types of words that contribute to predicting dementia risk. We can summarize key findings as follows:

1) We utilized three different machine learning methods for the speech data: MLP (Multi-Layer Perceptron), Random Forest, and SVM (Support Vector Machines). MLP yielded the highest accuracy, followed by SVM and Random Forest.
2) The Part-of-Speech (PoS) tags identified by our algorithm as significantly impacting Dementia closely align with the findings in clinical literature [21, 22, 23].
3) Our work produces a distinctive insight. Not only do we identify important PoS tags individually, but we also establish their importance in relation to each other. Random Forest has provided us with insights regarding the relative significance of PoS in speech. We discovered that the use of nouns holds the highest im-portance when it comes to predicting dementia, followed by Personal Pronouns (pro:per), 'Determiners' (det:art), and then adverbs (adv)
4) Another unique insight generated through Random Forest is that our data analysis indicates that determiners (the part of speech that modifies nouns or noun phrases and expresses the reference of the noun phrase in context) have a greater impact than verbs or adjectives. This differs subtly from the conventional wisdom and prevailing literature, which generally indicate that verbs and adjectives have a more pronounced influence.
5) Despite MLP (a type of Neural Network) achieving higher accuracy, Random Forest and SVM have a lower probability of overfitting i.e., performing extremely well in training scenarios but not achieving the same benchmarks in real-world scenarios. (Uddin S. et al. [33]). It is advisable to explore Random Forest or SVM further for real-life deployment of models.

6. OPEN RESEARCH AREAS

Scalability and Adaptability: A crucial aspect of effective machine learning models is their ability to scale and adapt to broader datasets and populations. Future work could explore applying our study to various datasets.

Model Generalization Assessment: It's important to analyze whether the model is overfitting to the training data. Further investigation in this area is necessary.

Cross-Linguistic Applicability: Expanding the study to include multi-lingual corpora of Part-of-Speech tags would allow us to assess the model's performance in languages other than English.

Exploring Diverse Machine Learning Techniques: While this study investigated the use of MLP, SVN, and Random Forest algorithms for dementia prediction, examining the effectiveness of other machine learning techniques remains an open area for research.

Integration with Acoustic Algorithms: Combining the model with acoustic algorithms (converting speech to text and then to Part-of-Speech Tags) presents another research opportunity. A key challenge here is ensuring that the response time of the combined model is practical for real-world applications.

7. CONCLUSION

We find that applying Machine learning methods to Parts-Of-Speech tags has promising potential in detection of dementia risk. Our models gave good accuracies and re-call. Not only that, but we also found that the reasoning used by our machine learning methodologies (as exhibited by Random Forest) clearly aligns with clinical literature about the impact of Part-Of-Speech in Dementia. This gives significant credibility to the nature of models.

With increasingly effective Speech-to-Text converters and rich Natural Language toolkits implementations available, models can be seamlessly integrated into the speech acquisition pipeline for detecting dementia risk.

The results of this research could find broad adoption through a mobile application employing various machine learning models. The aim of this app would be to capture speech patterns and assess the potential risk of dementia.

8. FUTURE WORK

To enhance the performance and robustness of our machine learning models, we propose the expansion of our approach to include the remaining data within the AphasiaBank corpus, as well as other textual transcripts. This broader dataset ensures that our models are not overly specialized (overfit) and are better equipped to handle real-world scenarios.

Moreover, our research has the potential for further refinement by incorporating additional dementia-related lifestyle parameters. By amalgamating these parameters with our machine learning techniques, we can create an ensemble of models. This ensemble approach enhances the comprehensiveness of our analysis, allowing us to capture a broader spectrum of factors that may contribute to dementia risk prediction. In doing so, we move closer to achieving a more holistic and reliable predictive tool for dementia risk assessment.

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